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Surrogate modeling of a permanent magnet synchronous machine finite element models based on artificial neural networks

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Surrogate modeling of a permanent magnet synchronous machine finite element models based on artificial neural networks

Background

- Physics-based modeling methods compromise between the run-time simulation efficiency and accuracy
  - E.g. finite element method (FEM) is accurate but slow, and electrical equivalent circuit method is fast but less accurate
- Surrogate modeling offer a way to avoid the trade-off between efficiency and accuracy
  - Machine learning (ML) and artificial neural networks (ANNs) enable developing surrogate models for numerous applications that require good computational performance
- In this study, an ANN surrogate model for simulating torque behaviour of a permanent magnet synchronous machine (PMSM) finite element model was developed

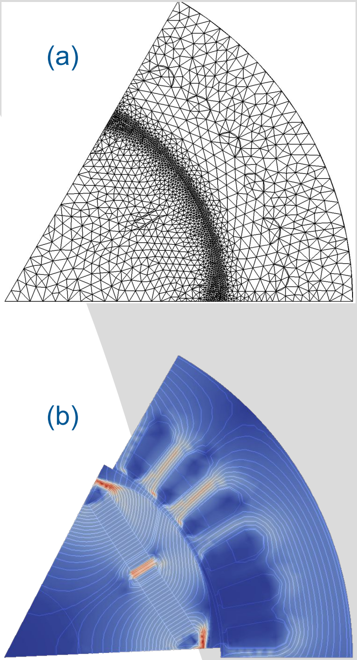
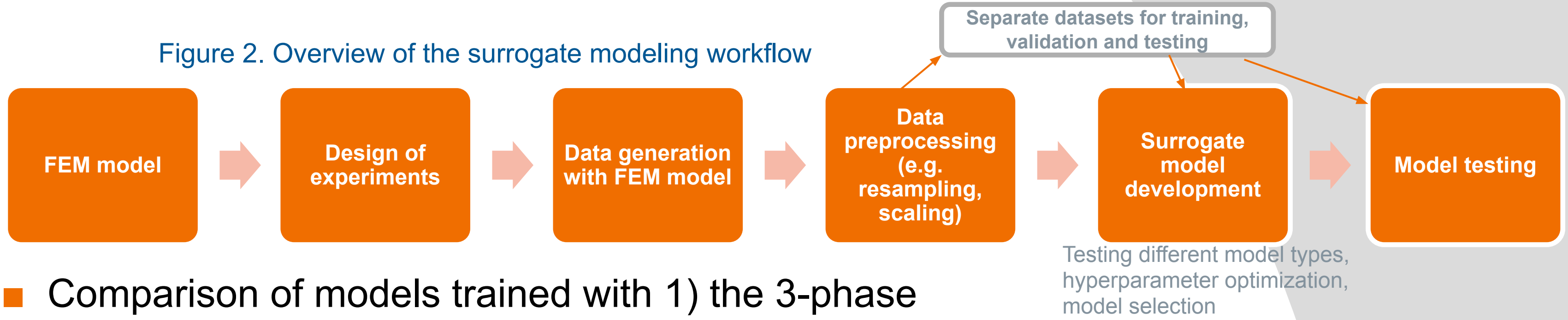


Figure 1. (a) FEM mesh, and (b) magnetic flux density and flux lines of the FEM solution

Acknowledgment: The work has been done in the Arrowhead Tools project, funded by European Commission and Business Finland, under grant 826452.

Surrogate modeling of a PMSM finite element models based on ANNs
Modeling workflow and data preparation

Figure 2. Overview of the surrogate modeling workflow



- Comparison of models trained with 1) the 3-phase current and 2) the following extracted features:
  - Absolute values of the three current values
  - Maximum value of the absolute values
  - 1st discrete difference of each of the three current signals

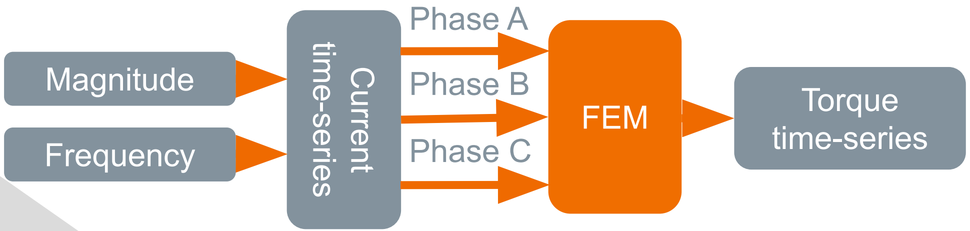


Figure 3. Data generation with FEM

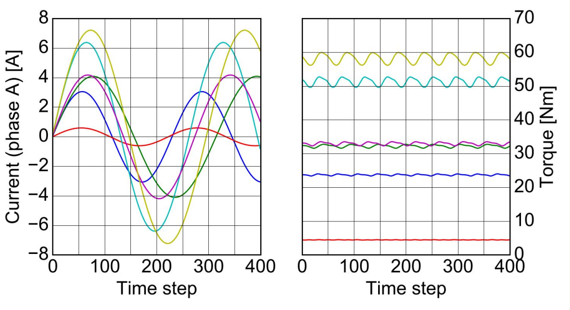


Figure 4. Resampled input (phase A) and output time series

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Surrogate modeling of a PMSM finite element models based on ANNs
Experiments

- Comparison between ANN and gradient boosting decision tree (GBDT):
  - ANN more suitable for EM applications, since its predictions smoother and continuous
  - The “resolution” of GBDT wasn’t high enough to produce smoother output

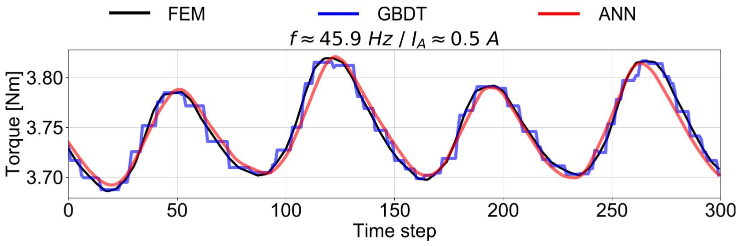

Figure 5. Example case of ANN and GBDT predictions.

- Sampling experiments with ANN – Comparison between randomized and grid sampling, and a combination of these two
  - Grid sampling dataset: ~200 cases
  - LHS-based randomized sampling: 50, 100, 200, or 300 cases
  - Validation and testing dataset: 150 and 190 cases
  - Combining grid and LHS samples resulted in the best accuracy, but for low currents in general, the ANN accuracy was worse, due to strong nonlinearity in that area

Training dataset	NRMSE avg [%]	NRMSE max [%]
LHS_50	4.1	38.0
LHS_100	2.2	28.0
LHS_200	2.0	29.9
LHS_300	1.6	29.6
GRID_196	3.2	16.4
GRID_196+LHS_100	1.4	11.5

Table 1. Test accuracy of ANN models trained with differently sampled training datasets.

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Hybrid model structure

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- Hybrid model structure was employed to increase the accuracy in low currents
- The magnitude of torque is almost linearly dependent on the current amplitude
  1. ANNs were trained to predict the ratio of torque to the current amplitude
  2. The actual torque value is computed as a post-processing step by multiplying the ANN output with the current amplitude

  ➡ The low current accuracy was improved to a sufficient level

Dataset	NRMSE avg [%]	NRMSE max [%]
Baseline (non-hybrid with extracted input features)	1.38	11.45
Hybrid with extracted input features	**1.14** (**-0.24**)	5.47 (**-5.97**)
Hybrid with original input features	1.77 (+0.39)	**4.42** (**-7.03**)

Table 2. Test accuracy of ANNs with different training setups. NRMSE was computed for each test case (n=190), and values shown here are the average and maximum

- Without hybrid structure, feature extraction was needed to improve the normalized root mean square errors (NRMSEs)
- With hybrid structure, the extracted features worked well, but with the original features NRMSE max was improved even more (with the cost of slightly worse NRMSE avg.)

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Surrogate modeling of a PMSM finite element models based on ANNs
Run-time efficiency of the developed surrogate model

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- Run-time efficiency:
  - FEM: avg. 146.5 s / case
  - ANN*: 56.1 **ms** / case (*hybrid model with the best accuracy)
  - ➢ The surrogate model is ~2600 times faster in average

- Surrogate* development took 32 h without parallelization

Training dataset	FE simulation [h]	ANN training [h]	Total [h]
LHS_100	17.9	2.2	20.1
GRID_196	21.8	5.5	27.3
GRID_196+LHS_100	25.9	5.7	31.6

Table 3. Breakdown of surrogate model development time. FE simulation time include simulations of training, validation and testing data

- ANN surrogates can be used to accelerate FEM-based engineering design tasks (surrogate model-based optimization), for example
  - Simulation-based surrogates can be also utilized in control applications and condition monitoring, for which they could be adapted using e.g. transfer learning

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